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RESEARCH ARTICLE

Examining the role of semiotics in social media-driven information campaigns

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Abstract

The rise of visually driven platforms like Instagram has reshaped how information is shared and understood. This study examines the role of social, cultural, and political (SCP) symbols in Instagram posts during Taiwan's 2024 election, focusing on their influence in anti-misinformation efforts. Using large language models (LLMs)—GPT-4 Omni and Gemini Pro Vision—we analyzed thousands of posts to extract and classify symbolic elements, comparing model performance in consistency and interpretive depth. We evaluated how SCP symbols affect user engagement, perceptions of fairness, and content spread. Engagement was measured by likes, while diffusion patterns followed the SEIZ epidemiological model. Findings show that posts featuring SCP symbols consistently received more interaction, even when follower counts were equal. Although political content creators often had larger audiences, posts with cultural symbols drove the highest engagement, were perceived as more fair and trustworthy, and spread more rapidly across networks. Our results suggest that symbolic richness influences online interactions more than audience size. By integrating semiotic analysis, LLM-based interpretation, and diffusion modeling, this study offers a novel framework for understanding how symbolic communication shapes engagement on visual platforms. These insights can guide designers, policymakers, and strategists in developing culturally resonant, symbol-aware messaging to combat misinformation and promote credible narratives.

Policy Significance Statement

This study demonstrates that social, cultural, and political (SCP) symbols embedded in Instagram posts play a significant role in shaping user engagement, perceptions of fairness, and the spread of information during misinformation campaigns. Through the integration of semiotic analysis, large language models, and epidemiological modeling, we find that symbol-rich content, particularly cultural references, contributes to greater trust and faster dissemination of messages. These findings offer valuable insights for social media governance by helping policymakers and platform designers enhance moderation systems and develop more effective strategies to counter misinformation. Emphasizing symbolic awareness in public communication and algorithmic audits provides a practical approach to strengthening digital resilience, supporting democratic discourse, and safeguarding information integrity during elections and other critical civic moments.

1. Introduction

The interpretive richness of visual media creates challenges for traditional text-based analysis, especially in online environments where meaning is increasingly communicated through images. As Chandler (2002) explains, images carry both literal and connotative meanings, allowing them to function as powerful conveyors of complex narratives. On platforms like Instagram—with over 1 billion monthly and 500 million daily active users—visual content has become central to shaping public opinion and engagement across social, cultural, and political domains (Rejeb et al. 2022). Research has shown that such imagery can evoke a wide range of emotional responses (Schreiner et al. 2021), highlighting the limitations of relying solely on textual content to understand user behavior or interpret the broader narrative being communicated. This limitation is particularly relevant in the context of misinformation, where visual framing can significantly influence perceptions of legitimacy and trust. Gurung et al. (2024b) found that social media content titles often fail to capture the nuanced messages encoded in accompanying visuals, reinforcing the need for a more holistic, multimodal approach to content analysis. To address this gap, our study investigates how social, cultural, and political (SCP) symbols embedded in Instagram images shape engagement and influence the perceived integrity of posts related to Taiwan's 2024 election anti-misinformation campaign.

Leveraging the multimodal capabilities of advanced large language models (LLMs), specifically GPT-4 Omni (GPT-4o) and Gemini Pro Vision, we extract and classify SCP symbols from Instagram posts. We then analyze how these symbols affect user engagement—measured via likes—and how closely user-generated text aligns semantically with LLM-generated content descriptions. We also apply the SEIZ epidemiological model to examine how symbolic content influences the spread of posts, capturing transitions between states of susceptibility, exposure, infection (engagement), and skepticism.

Our study addresses the following research questions:

1. Does the presence of social, cultural, or political (SCP) symbols increase user engagement?
2. Does the effect of SCP symbols on engagement vary with follower count?
3. Do SCP symbols shape perceptions of fairness and cheating in online discourse?
4. Do SCP symbols accelerate the dissemination of content on social media?

Our analysis of 3097 Instagram posts reveals that SCP symbols—particularly cultural ones—significantly enhance engagement and fairness perceptions. Posts containing all three types of symbols exhibited the highest average likes and the fastest diffusion, according to SEIZ modeling. Importantly, these effects were consistent across accounts regardless of follower count, indicating that symbolic richness, rather than audience size, is a key driver of engagement and narrative spread. These findings underscore the importance of incorporating semiotic analysis into both platform governance and misinformation response strategies, particularly in visually driven digital ecosystems.

2. Background

Taiwan's 2024 election encountered substantial misinformation challenges, including false allegations of voter fraud and miscounted results. As ballots were tallied on January 13, rumors of vote fabrication spread, raising concerns about election integrity. However, Taiwan successfully mitigated a potential crisis through a "whole-of-society" approach. Fact-checking organizations swiftly debunked false claims, the Central Election Commission clarified discrepancies, and YouTube influencers rapidly countered misinformation. This coordinated response helped safeguard election integrity and restore public confidence.

Figure 1, based on publicly available articles (Klepper and Wu 2024; MyGoPen 2024), illustrates the timeline of these actions, with misinformation marked in orange and debunking efforts in blue. While early research efforts focused on YouTube and TikTok, Instagram emerged as the primary source of anti-misinformation data for this study due to the large volume of relevant content available.

3. Literature review

Semiotics, the study of signs and symbols in communication, provides a foundational lens for analyzing how meaning is constructed and interpreted through visual media. As Chandler (2002) explains, images operate on two primary levels: the denotative (literal meaning) and the connotative (associative meaning).

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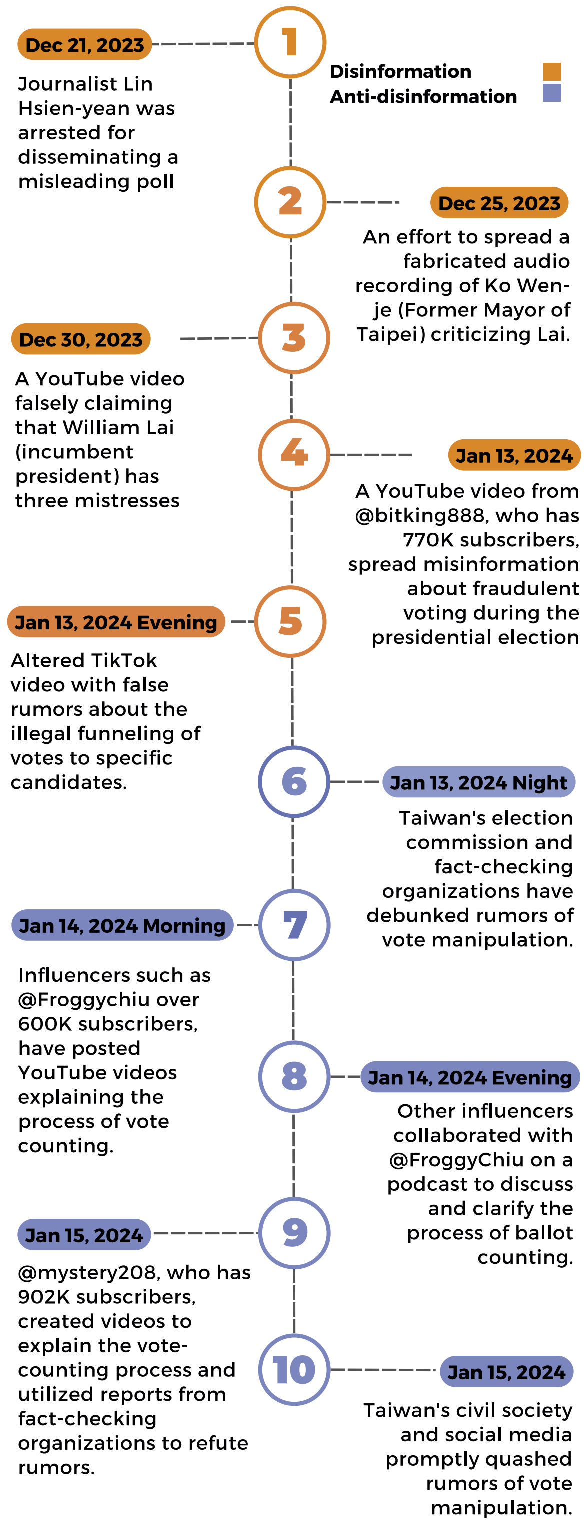

Figure 1. *Timeline depicting the spread and rapid debunking of election-related misinformation in Taiwan. Orange depicts the misinformation campaign while blue depicts the anti-misinformation campaign.*

Symbols embedded within images can evoke a wide range of emotions and cultural associations, often extending far beyond their surface representation. For instance, a dove may represent peace or spiritual freedom depending on its cultural context.

In the digital era, especially on image-centric platforms like Instagram, the symbolic power of visuals has intensified. Van Leeuwen (2005) argues that social media amplifies the connotative force of images, while Rose (2022) emphasizes the role of multimodality, noting that political symbols are interpreted through the viewer's ideological and cultural filters. These interpretations can reinforce existing beliefs and shape broader political narratives. This aligns with Hall's encoding/decoding theory, which posits that media messages are encoded with preferred meanings by content creators but are actively interpreted by audiences, who may accept, negotiate, or oppose those meanings depending on their cultural context Hall (2014).

Symbols used in social media often have deep historical and cultural roots. Social symbols such as gestures or rituals communicate shared meanings and contribute to social cohesion Turner (1967). Cultural symbols, including flags and religious icons, encapsulate collective identity and values, serving as markers of tradition and belonging Dadze-Arthur (2017). Political symbols, such as slogans and emblems, express ideologies, authority, and mobilization efforts Mosse (2023). In today's digital landscape, these symbols are dynamic and fluid, frequently repurposed or contested in real time. They play a pivotal role in identity formation, public discourse, and collective action. As Johann (2022) notes, symbols in the digital age often transform into viral content or memes, influencing public opinion and driving sociopolitical change. Consequently, the need for computational analysis of these symbolic elements has become increasingly urgent.

Entity extraction from images is a key step in this analytical process. Traditionally, this task has been addressed through computer vision techniques such as object detection and classification using convolutional neural networks (CNNs). Early architectures like AlexNet, VGGNet, and ResNet laid the groundwork for extracting visual patterns and hierarchies Ren et al. (2015). More recently, the emergence of large language models (LLMs) has significantly advanced this field. Unlike conventional models, LLMs such as GPT-4 can process multimodal inputs and generate semantically rich outputs. They not only enhance contextual understanding but also offer detailed visual descriptions and entity recognition capabilities OpenAI (2024).

LLMs have transformed artificial intelligence by enabling high-accuracy text generation and comprehension across diverse contexts. Models like GPT-3 and GPT-4, trained on extensive datasets, excel at identifying linguistic patterns and semantic nuances Brown et al. (2020). Their applications extend to data annotation, autonomous agents, and content moderation. In annotation tasks, LLMs can consistently label large datasets with minimal human oversight, improving scalability and reducing errors Cui et al. (2022). For visual data, multimodal models such as CLIP (Contrastive Language-Image Pre-training) and Gemini bridge textual and visual domains. CLIP enables alignment between image content and language descriptions, facilitating tasks like captioning and symbolic recognition Radford et al. (2021). Gemini extends this functionality across audio, video, and text, offering a robust solution for multimodal reasoning and analysis Anil et al. (2023). In addition to symbol detection, it is essential to understand how symbolic content spreads across digital networks. To this end, researchers have adapted epidemiological models, originally developed to study infectious diseases, for use in analyzing the spread of information and misinformation on social media. The SIS (Susceptible-Infected-Susceptible) model captures recurring user engagement patterns, while SEIR (Susceptible-Exposed-Infected-Recovered) introduces a latency phase to represent delayed user action Daley and Kendall (1964); Moreno et al. (2002); Lerman and Ghosh (2010). The SEIRS model adds resusceptibility, modeling the reactivation of users Zhao et al. (2011); Vosoughi et al. (2018). Among these, the (Susceptible-Exposed-Infected-Skeptic (SEIZ) model offers particular relevance for narrative propagation. As shown by Gurung et al. (2024a), SEIZ effectively captures how users may engage with, resist, or reject information. This makes it especially suitable for modeling misinformation spread, where skepticism plays a key role in moderating engagement.

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4. Methodology

The following section outlines the data collection process on Instagram and explains the methodology behind the experiments. It highlights the extraction of social, political, and cultural (SCP) symbols and evaluates the performance of different large language models in this context. Finally, we explore key experiments, including modeling information spread and comparing factors such as trust and emotion, that provide insights into our approach and findings.

4.1. Data collection

In this section, we outline the methodology for collecting data on Taiwan's election anti-misinformation campaign from Instagram. Our data collection followed a multi-stage, iterative approach designed to comprehensively capture information on the election and the related anti-misinformation efforts. The process began with identifying key seed terms based on the news sources discussed in Section 2.

Next, we constructed a co-occurrence network and performed topic clustering using Latent Dirichlet Allocation (LDA), as illustrated in Figures 2 and 3, from the seed posts collected. This analysis identified distinct communities centered around political figures (e.g., Lai Ching-te, Takaka Kiyoshi) and political entities (e.g., the Democratic Progressive Party (DPP) and Kuomintang). Insights from this network analysis and topic clustering guided the development of a refined keyword list incorporating terms related to Taiwan's anti-misinformation campaign.

Using these expanded keywords, we conducted a second round of data collection. To ensure comprehensive coverage, we employed a snowball sampling approach, allowing the dataset to grow dynamically as new relevant hashtags and topics emerged. The final set of hashtags and keywords is detailed in Table 1.

4.2. Extraction of social, cultural, and political symbols

Large language models (LLMs) have been widely applied across various domains, including healthcare and education. One of their key strengths lies in their ability to understand context, significantly enhancing Natural Language Understanding (NLU) capabilities, as noted by Liu et al. (2023). Additionally, Qi et al. (2023) highlights the multimodal capabilities of these models, emphasizing distinct

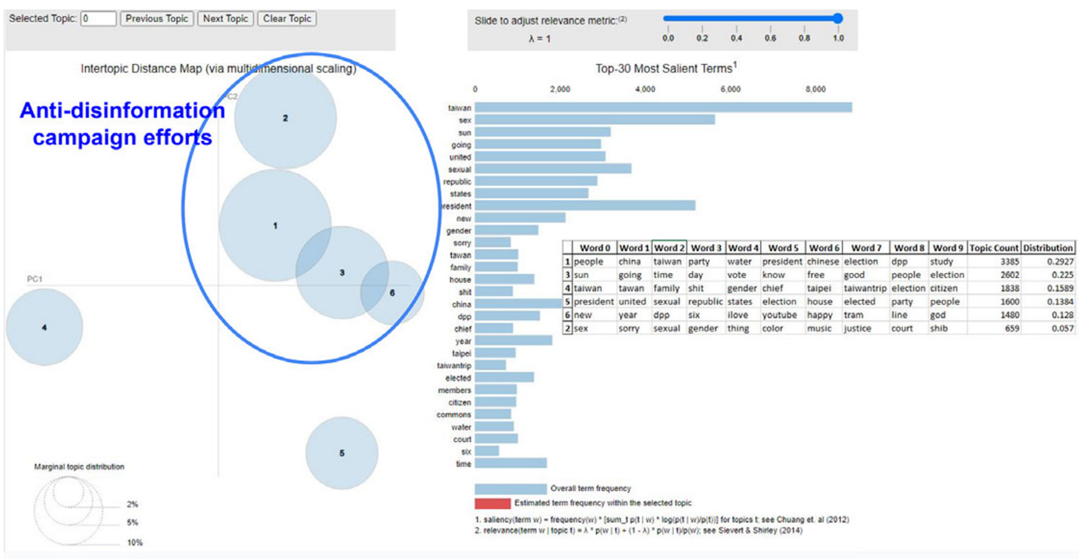

Figure 2. *Topic Clustering using LDA showing keywords.*

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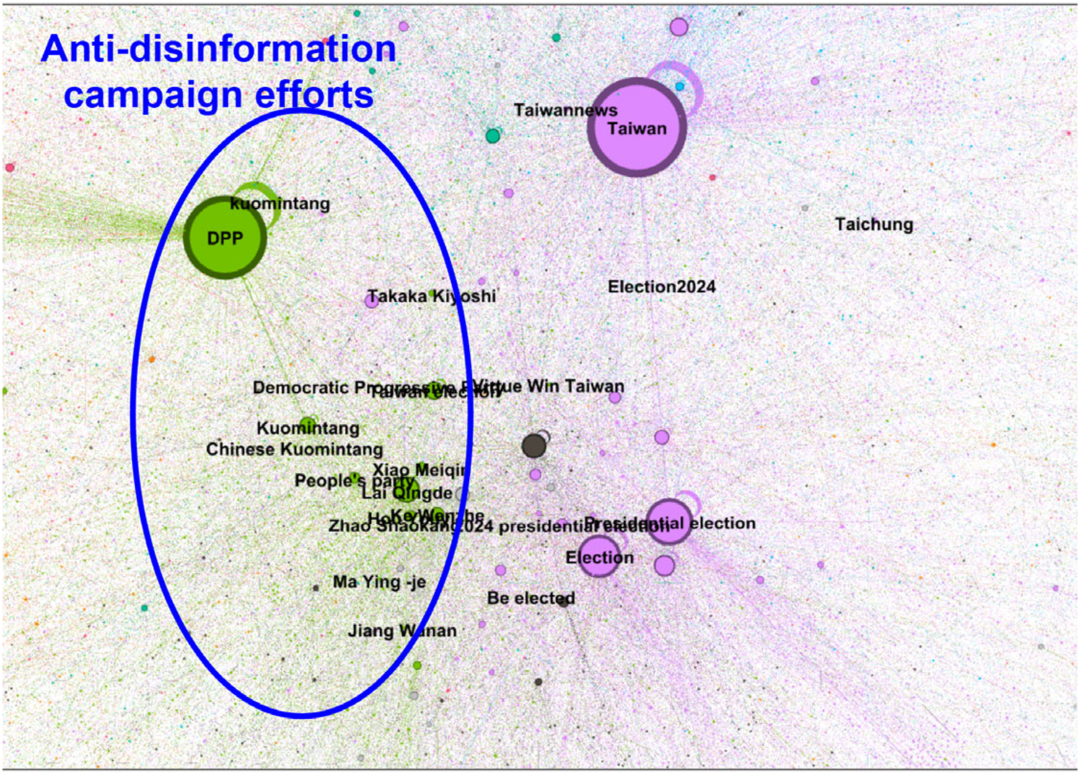

Figure 3. *Communication network showing communities formed using keywords and hashtags.*

Table 1. *Hashtags and keywords used for data collection from January 13th to 27th, 2024*

Keywords and Hashtags.
'inkthafreedomparty', 'LaiChingTe', 'kuomintang', 'taiwanstrait', 'williamlai', 'democratic progressiveparty', 'laichingte', '拾人2024', 'TsaiIngwen', 'KoWenJe', 'TaiwanLegislative YuanElection', '民主進步黨', '蔡英文', '柯文哲', '侯友宜', '柯P', '民政黨', '民政黨主席', 'taiwanelection2024', 'votefortaiwan', 'tsaiingwen', 'DPP', 'Chinese Kuomintang', 'bikhimxiaosiao', 'Takaka Kiyoshi', 'bikhimhsiaosiao', 'ilovetaiwan', 'everydaytaiwan', 'legislativeyuan', 'TaiwanElection2024', 'KuomintangParty', 'ChinaTaiwanAffairsOffice', 'DPPtaiwan', 'Taiwaneseartists', 'TaiwanDPP', 'Ma Ying-jeou', 'Jiang Wanan', 'Democratic ProgressivePartyTaiwan', 'TaiwanNews', 'TaiwanPresidentialElection2024', '16thPresident', 'HouYuIh', 'komingtan', 'whiteterror', 'chiangkaishek', 'kuomingtang', '白色恐?', '分行', 'Myopgen'

advantages: GPT-4 excels in delivering precise and concise responses, while Gemini is adept at generating comprehensive, richly detailed answers supplemented with relevant imagery and links. Recent advancements, such as Gemini Pro-Vision and GPT-4o, have further expanded these capabilities to include image analysis. In our study, we leveraged these advanced models to extract social, cultural, and political (SCP) symbols from images.

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We briefly discuss the parameters used by LLMs to extract these symbols. Despite variations in overall size, GPT-4o and Gemini Pro-Vision share several key parameter settings. Below, we highlight the parameters consistently applied to both models to ensure uniform performance. It is important to note that these represent only basic tuning, as the primary focus of this paper is not on how these models compare in symbol extraction. Instead, we aim to observe how these models, in their standard configurations, approach the task of extracting these symbols.

- Temperature: This parameter controls the randomness of responses. A lower temperature produces more predictable outputs, while a higher value increases variability. For both models, the temperature was set to 0 to prioritize predictability and consistency.
- Frequency Penalty: This setting reduces the likelihood of repeated words or phrases by penalizing frequent tokens. In both models, the frequency penalty was set to 0, allowing for a natural language flow without discouraging necessary repetition.

The prompt employed for both models was the following:

> "Visualize yourself as a proficient linguist tasked with analyzing an Instagram image. Your goal is to identify and categorize three forms of 'Symbolic Communication' present in the image: 'Social,' 'Cultural,' and 'Political.' If a classification is unclear, assign it a value of '0.' For instance, if 'Social' and 'Cultural' are present but 'Political' is not, your output should be formatted as: {'Social': 1, 'Cultural': 1, 'Political': 0}. Justify each assigned value with reasoning."

Figure 4 showcases examples of various combinations of social, cultural, and political (SCP) symbols as interpreted by the Gemini and GPT models. This comparison highlights both the alignments and divergences in how the two models evaluate and classify these symbols within the given context.

In the first row of images, the models largely agree on their identification of most symbols, with one notable exception: the interpretation of a flower in the first image. Gemini attributes cultural significance to the flower, identifying it as a meaningful symbol, while GPT does not assign it any specific symbolic

Figure 4. *Exploration of images comparing various combinations of social, cultural, and political (SCP) symbols and their performance in GPT-4o and Gemini Pro-Vision.*

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meaning, highlighting subtle differences in how the models prioritize cultural context and aesthetic elements. The flower's vibrant variety of colors and species reflects the harmony Taiwan seeks to cultivate within its society and environment, making it particularly relevant to our case study on an anti-election misinformation campaign, as it symbolizes unity, trust, and the public's confidence in the electoral process and commitment to peace.

In the second row, the disparities between the models become more evident. A clear example is the second image in this row, which features a dragon. GPT identifies the dragon as a cultural symbol, likely drawing on its traditional and historical associations, whereas Gemini does not classify it as such. Furthermore, the same image reveals differences in how the models interpret political symbolism. According to GPT, the dragon's menacing posture toward an individual holding the Taiwanese flag reflects political tension, symbolizing the strained relationship between China (represented by the dragon) and Taiwan (represented by the flag-bearer). In contrast, Gemini interprets the image as Taiwan's assertion of sovereignty and national identity in the face of perceived dominance or aggression from China. While both models recognize political undertones, their interpretations emphasize different aspects: GPT focuses on the antagonistic visual elements, while Gemini highlights the symbolic representation of resistance and identity.

The most significant divergence occurs in the interpretation of the final image. GPT categorizes this image as encompassing all three types of symbols—social, cultural, and political. According to GPT, the image conveys social unity through the large gathering of people, cultural pride through the traditional illuminated structure, and political expression through the presence of flags and banners and through the act of public assembly. In contrast, Gemini does not identify any symbols in this image. This stark difference underscores the models' varying thresholds for detecting and classifying complex, multi-layered symbolic elements, especially in intricate visual compositions.

Additionally, we extended our analysis to examine the expression of trust and emotion within the comments on these posts, leveraging models such as GPT-4 and Gemini. Unlike the SCP extraction process, this analysis was performed without any parameter tuning, ensuring that the outcomes reflected the models' default configurations. This approach allowed us to evaluate the models' inherent ability to interpret and respond to emotional cues and trust indicators embedded in the data.

4.3. Categorization by symbol number

The images were categorized based on the diversity of symbols present in each post, without allowing for overlap (i.e., mutually exclusive):

- **Category 0**: Posts with no symbols.
- **Category 1**: Posts containing a single symbol of any type—Social (S), Cultural (C), or Political (P).
- **Category 2**: Posts containing symbols from two of these types.
- **Category 3**: Posts containing symbols from all three types.

The distribution of posts categorized based on symbol diversity is shown in Figure 5.

4.4. Categorization by symbol type

The images were categorized based on the presence of each symbol type, allowing for overlap (i.e., mutually inclusive):

- **Images with no symbol**
- **Images with social symbol**
- **Images with cultural symbol**
- **Images with political symbol**

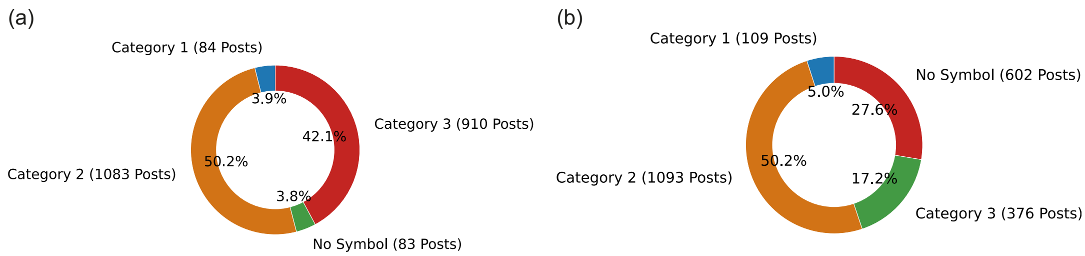

Figure 5. *Data distribution of Instagram posts related to Taiwan's anti-election misinformation campaign.*

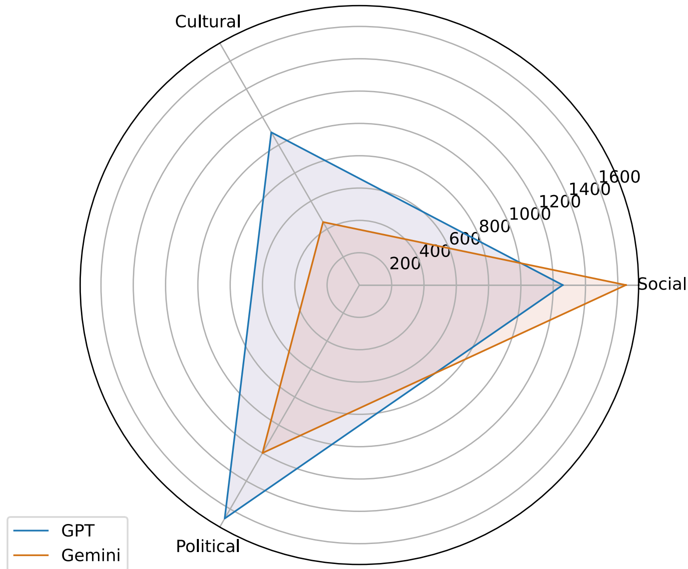

Figure 6. *Comparison of social, cultural, and political entities extracted by GPT-4o and Gemini Pro-Vision.*

The categorization by symbol type, as shown in Figure 6, is based on the type of symbol extracted by GPT and Gemini.

4.5. Adapting SEIZ model for Instagram data

To model the spread of resonance on Instagram using an epidemiological approach, it is crucial to select an appropriate model and parameters that accurately reflect the complexity and realism of the problem. Our methodology draws a parallel between the spread of likes on Instagram and the dissemination of toxicity and rumors on social media (Obadimu et al. 2020). People's ideologies are complex, and when they are exposed to news or rumors, they may hold different views, take time to adopt an idea, or even be skeptical of some of the facts. In these situations, they might be persuaded to propagate a story or share it only after careful consideration. Additionally, it is quite conceivable that an individual can be exposed to a story yet never share it themselves.

According to Jin et al. (2013), the SEIZ model has the following rules: Susceptibles, once exposed to a post, transition into the Exposed compartment. Individuals in the Exposed compartment may transition to the Infected class, either after further contact with the Infected or without additional contact through self-adoption, or may become Skeptics. All transitions occur at a specific rate.

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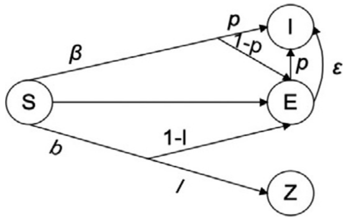

Figure 7. *SEIZ model showing the flow between Susceptible (S), Exposed (E), Infected (I), and Zero (Z) states with transition rates.*

Specifically, we identify the following groups of Instagram users for the SEIZ model, which are modeled using equations 1 and demonstrated in Figure 7.

- $S(t)$: Susceptible users who have not seen the narrative content yet but might encounter and engage with it, even if they do not follow infected users.
- $E(t)$: Exposed users who have seen the narrative content and are evaluating whether to share it, typically following infected users.
- $I(t)$: Users actively posting about or amplifying the narrative content.
- $Z(t)$: Users who delay posting after exposure or have stopped actively engaging with the narrative content.

The following system of Ordinary Differential Equations (ODEs) represents the SEIZ model (Jin et al. 2013), demonstrated in Figure 7:

$$\begin{cases} \frac{dS}{dt} = -\frac{\beta SI}{N} - \frac{\gamma SZ}{N}, \\ \frac{dE}{dt} = \frac{(1-p)\beta SI}{N} + \frac{(1-\lambda)\gamma SZ}{N} - \frac{\eta EI}{N} - \varepsilon E, \\ \frac{dI}{dt} = \frac{p\beta SI}{N} + \frac{\eta EI}{N} + \varepsilon E, \\ \frac{dZ}{dt} = \frac{\lambda\gamma SZ}{N}. \end{cases} \tag{1}$$

To apply the SEIZ model from equations (1), key parameters like contact rates (β, γ, η) must be defined, along with initial values for $S(t_0)$, $E(t_0)$, $I(t_0)$, and $Z(t_0)$. The implementation was done in Python using *scipy.optimize* for least-squares fitting and *odeint* for solving the ODEs. We used Nelder–Mead optimization within *scipy.optimize.minimize* to ensure parameter convergence by minimizing the difference between the Infected compartment (I) and the corresponding Instagram data, $|I(t) - posts(t)|$. We tracked weekly cumulative post counts to set optimization boundaries.

5. Results

This section presents the results obtained from the methodology outlined in Section 4. We begin by examining the challenges encountered by the models in extracting SCP elements from the provided images. The extraction process required the models to identify and classify complex visual elements across diverse domains. This task proved particularly difficult when the elements were subtle, ambiguous, or embedded within intricate contexts that challenged model interpretation.

While both models demonstrated strong overall performance, certain images posed significant difficulties and remained unprocessable. Notably, the challenges varied between the models, with the GPT-4o model facing considerably more obstacles than the Gemini Pro Vision model. The GPT-4o model

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Table 2. *Summary of image analysis by GPT-4o and Gemini-Pro-Vision*

Description	Count
Total Images	3097
Images Analyzed by GPT–4o	2160
Images Analyzed by Gemini-Pro-Vision	2180
Unprocessed Images by GPT–4o	937
Unprocessed Images by Gemini-Pro-Vision	917

exhibited a higher failure rate, likely due to differences in its underlying architecture and training data. In contrast, the Gemini Pro Vision model, despite its own limitations, showed greater resilience and successfully processed a broader range of image types.

Table 2 provides a detailed comparison of the total number of images processed by each model, along with the number of images that could not be analyzed. This comparison highlights the performance differences between the two models and emphasizes the unique challenges involved in extracting SCP symbols from visual data.

5.1. The impact of SCP symbols on engagement in instagram posts

Our analysis reveals a strong correlation between the number of SCP symbols in posts and higher user engagement, as measured by the number of likes as seen in Figure 8. This addresses **RQ 1**, showing that posts with more symbolic elements consistently attract greater interaction from users.

The positive relationship between symbol count and engagement was observed in both the GPT and Gemini models, with only minor variations. This consistency across models strengthens the reliability of our findings, demonstrating that diverse symbolic content in Instagram posts significantly boosts user engagement.

We conducted a *t*-test to compare engagement levels between posts with and without SCP symbols as extracted by GPT 4o. The analysis yielded a *p*-value of 2.39×10^{-6}, indicating a statistically significant difference in the number of likes between posts containing SCP symbols and those without.

Furthermore, posts incorporating cultural symbols were found to attract the highest number of likes, followed by those with social and political symbols as seen in Figure 9.

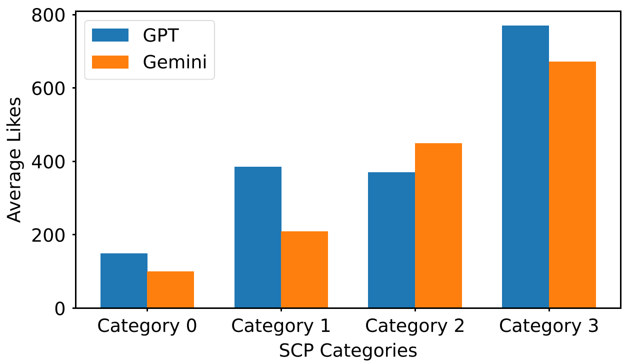

Figure 8. *Categorical comparison of posts based on the number of symbols. Posts containing all three symbols (Category 3) received the highest average likes, followed by posts with two symbols (Category 2), one symbol (Category 1), and no symbols (Category 0). These results are consistent for both the Gemini Pro-Vision and GPT-4o models.*

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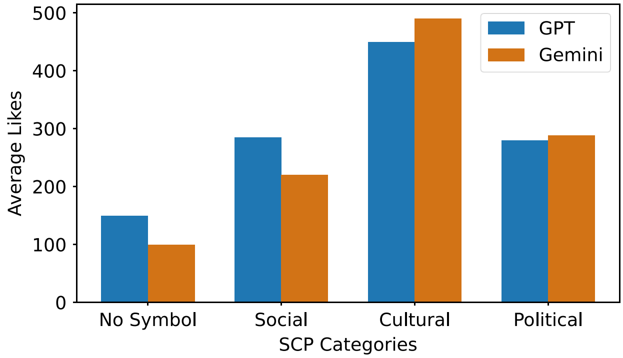

Figure 9. *Comparison of social, cultural, and political symbols extracted by Gemini Pro-Vision and GPT-4o. Cultural symbols received the most likes, followed by social and political symbols. Posts containing no symbols received the fewest likes, with a minor discrepancy in the social category between the Gemini Pro-Vision and GPT-4o models.*

5.2. The impact of follower count on engagement with SCP symbols

Building on our engagement analysis, we found that Instagram posts containing all three categories of symbolic content consistently generated higher levels of user interaction, as measured by the number of likes. Among these, cultural symbols exhibited the strongest association with engagement. This prompted a key question: Is the observed engagement effect influenced by the size of a user's audience, or does symbolic richness drive interaction regardless of follower count?

To investigate this, we conducted an analysis comparing follower counts across posts in each SCP symbol category. As shown in Figure 10, follower count distribution was relatively uniform across the categories. This suggests that account size alone does not explain the variation in engagement. In other words, high engagement, particularly in posts with rich symbolic content, appears to be driven more by the characteristics of the content than by the number of followers. These results indicate that the engagement effect of SCP symbols does not significantly vary with follower count and instead depends primarily on the symbolic nature of the content.

Additional analysis revealed that users posting politically themed content tended to have the highest follower counts. As illustrated in Figure 11, posts featuring cultural symbols consistently achieved the highest engagement across all follower ranges. This suggests that cultural symbolism may have broader appeal and may resonate more deeply with users, regardless of the reach of the account.

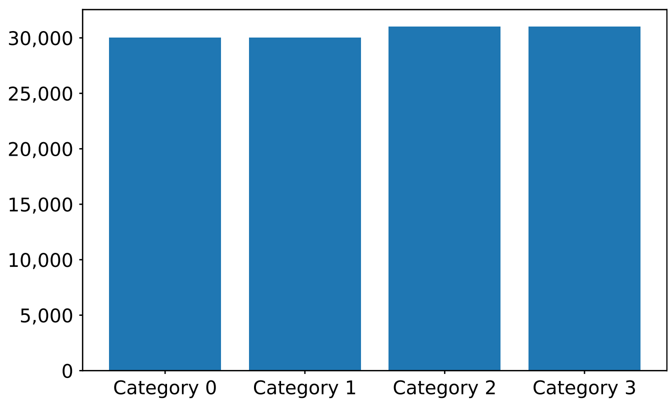

Figure 10. *Comparison of followers across categories based on the number of symbols. The distribution of followers across categories is relatively uniform.*

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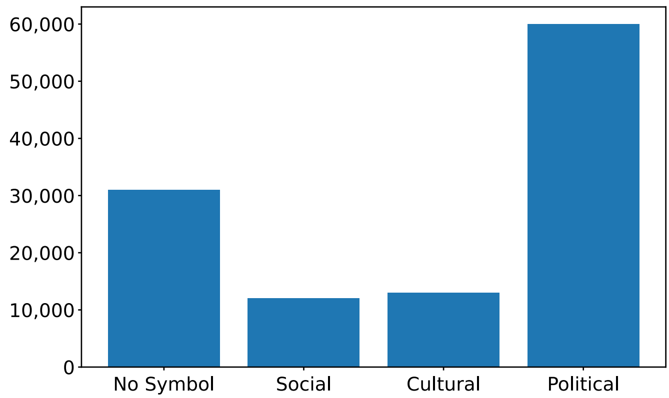

Figure 11. *Comparison of followers across categories based on the classification of symbols. Users posting political symbols had the highest number of followers.*

These findings suggest that the impact of SCP symbols on engagement is largely independent of follower count. They support the conclusion that content quality, and specifically symbolic richness, plays a more critical role in driving interaction than audience size alone, addressing **RQ 2**.

5.3. The role of SCP symbols in representing fairness and cheating

In this section, we examine whether the use of social, cultural, and political (SCP) symbols influences how fairness and cheating are perceived in social media content. This question is especially relevant in the context of misinformation campaigns, where issues of trust, manipulation, and legitimacy are central. Understanding how symbolic elements shape these perceptions is crucial when dealing with sensitive topics, such as election integrity.

Figure 12 presents the relationship between the number of SCP symbols in Instagram posts and the corresponding fairness and cheating scores, as interpreted by both the GPT-4o and Gemini Pro-Vision

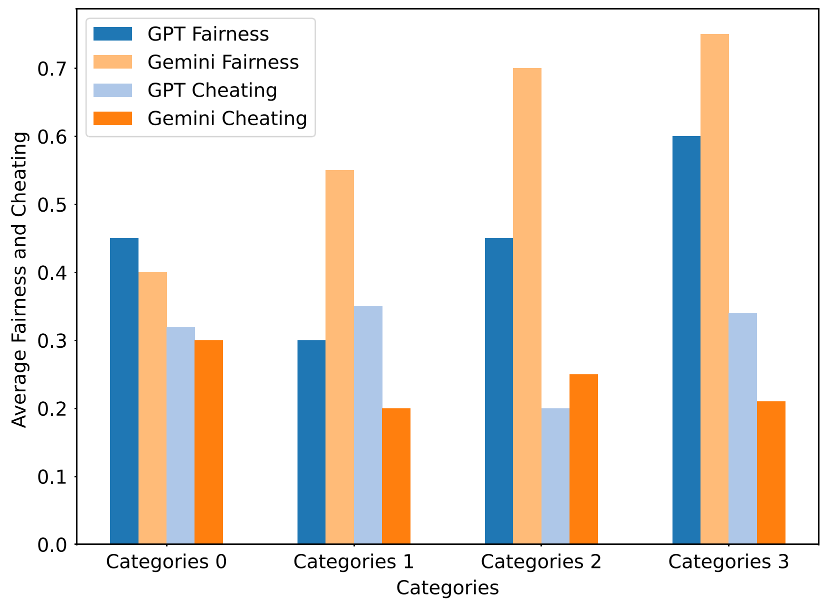

Figure 12. *Comparison of posts categorized by the number of symbols, showing that posts with all three symbols (Category 3) received the highest average fairness ratings from both the GPT and Gemini models.*

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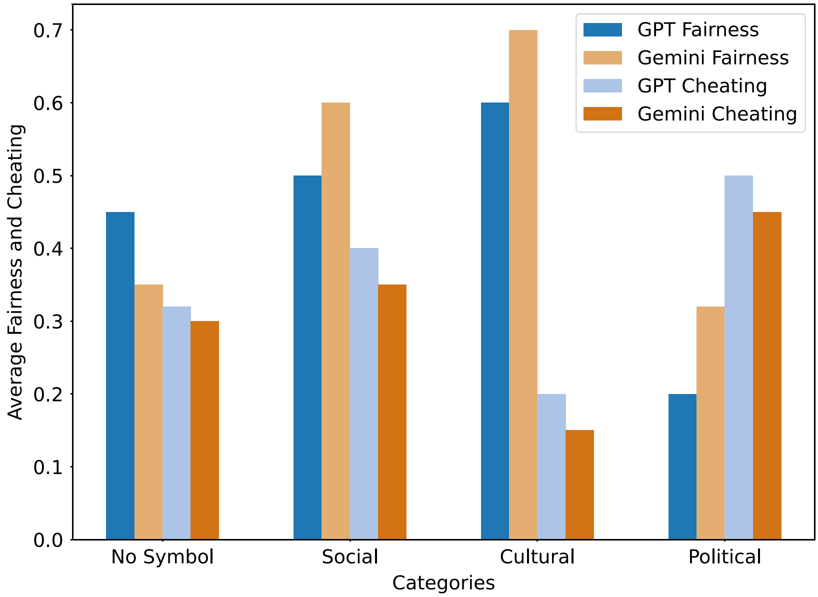

Figure 13. *Comparison of social, cultural, and political symbols identified by Gemini Pro-Vision and GPT-4o, showing that cultural symbols received the highest fairness ratings from both models.*

models. The results indicate a general increase in perceived fairness as the number of symbolic elements rises. Posts without any symbols (Category 0) initially scored higher in fairness than those with a single symbolic reference (Category 1). However, fairness perceptions improved significantly in Categories 2 and 3, where posts included two or more symbolic dimensions.

Figure 13 further explores the effect of individual SCP symbol types on fairness and cheating perceptions. Cultural symbols, in particular, were consistently associated with the highest fairness scores across both models. This suggests that cultural content may be especially effective in enhancing the perceived integrity and trustworthiness of posts. On the other hand, posts lacking symbolic content consistently received the lowest fairness ratings.

These findings demonstrate that symbolic content, particularly cultural symbolism, plays an important role in shaping how fairness is perceived by audiences. They directly address our research question **RQ 3**, confirming that both the presence and type of SCP symbols can meaningfully influence expressions of fairness in online discourse, especially in contexts involving sensitive or contested information.

5.4. Epidemiological modeling of anti misinformation posts in Instagram

To evaluate the success of posts in terms of dissemination, we utilized the SEIZ model. We investigated whether posts with the highest SCP symbols and those with greater similarity between user-generated text and LLM-generated descriptions had higher dissemination rates. The analysis produced the following results: in both experiments, our data fitting resulted in a minimum error rate as seen in Tables 2 and 3, indicating that Instagram data can be effectively modeled using the given epidemiological model. We observed that, from day 1 to day 4, both categories reached their peak dissemination, suggesting that in anti-misinformation campaigns, posts debunking misinformation tended to have a high infection rate and grow rapidly as soon as they were exposed on the platform.

In the first experiment, we assessed whether a higher number of SCP symbols led to higher infection rates. High correlation values signify a strong fit between the model and actual engagement data, implying effective prediction of information spread. Low relative error (E_{rel}) and mean absolute error (MAE) indicate accurate modeling with minimal deviations, crucial for assessing rapid and extensive engagement

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Table 3. *SEIZ model fitting results for different numbers of social, cultural, and political symbols in Instagram posts*

Category	E_{rel}	Correlation	MAE
Category 4	0.0041	0.9960	0.3
Category 3	0.0131	0.9711	10.6
Category 2	0.0101	0.9821	7.1
Category 1	0.0576	0.7502	3.3

spread. Among the categories analyzed, posts featuring all symbols exhibited the highest infection rate, with a near-perfect correlation of 0.9960, the lowest MAE of 0.3, and an infection rate of 0.3. This indicates that posts containing SCP symbols spread quickly and widely, resonating strongly with users and achieving higher engagement, which thus addresses our **RQ 4**. Conversely, posts without symbols showed the lowest correlation at 0.7502, a higher E_{rel}, and the lowest infection rate of 0.15. These findings are consistent with the SEIZ model's principles, where high infection rates signify rapid and extensive dissemination of information, making the category with all three symbols the most effective in spreading content among users. Figure 14 illustrates the model fit for posts without SCP symbols, while Figure 15 shows the model fit for posts with all symbols.

6. Policy implications

The findings from this study provide actionable insights for policymakers, platform developers, and researchers working at the intersection of data governance, algorithmic accountability, and digital resilience. Our analysis demonstrates that symbolic content embedded in social media posts, particularly social, cultural, and political symbols, significantly influences user engagement and perceptions of fairness. Cultural symbols, in particular, are associated with increased trust in content, suggesting that visual elements are not only aesthetic features but also critical cues in shaping how users interpret the legitimacy of information.

Given this, content moderation systems should be enhanced to include symbolic awareness. Traditional text-based moderation may miss the deeper narrative cues carried by images. Integrating multimodal

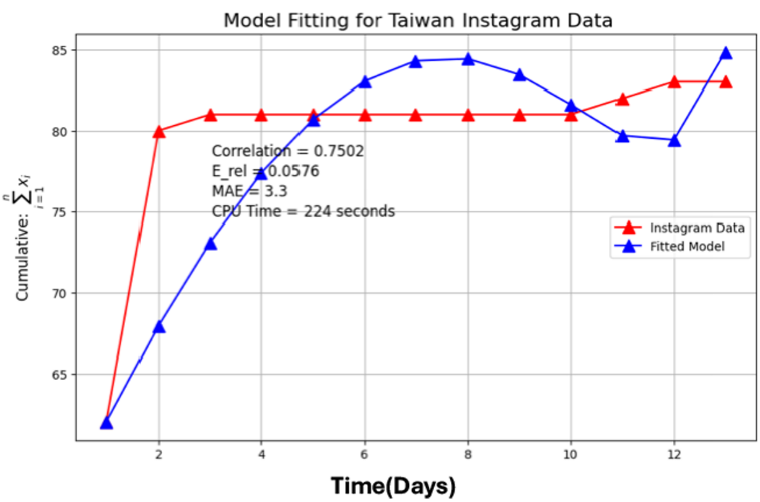

Figure 14. *SEIZ model fitting for Instagram posts with no social, cultural, and political symbols.*

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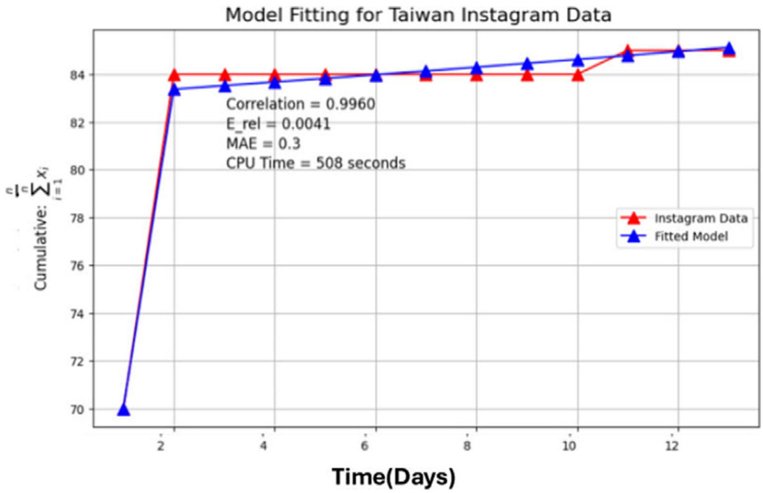

Figure 15. *SEIZ model fitting for Instagram posts with all three social, cultural, and political symbols.*

language models such as GPT-4o and Gemini Pro Vision allows for better detection of symbolic content and improves the ability of platforms to distinguish between benign cultural expression and potential misinformation. These models can enrich platform moderation capabilities by recognizing symbols that evoke collective identity, political stance, or social sentiment.

The strategic use of symbolic content also has implications for public communication. Campaigns designed to counter misinformation would benefit from incorporating culturally resonant imagery that aligns with the values and experiences of their target audiences. Fact-checking organizations and electoral authorities can improve outreach and influence by producing symbol-rich content that resonates on an emotional and cultural level. This can help build trust and increase the reach of corrective information, especially during elections or in times of social unrest.

In addition, our use of the SEIZ epidemiological model reveals that symbolic content significantly accelerates the spread of narratives on social media. Posts with multiple types of symbolic content exhibited higher infection rates and faster diffusion compared to those without such elements. This insight supports the development of predictive tools that can monitor and respond to emerging misinformation trends based on their symbolic structure. Real-time dashboards informed by narrative contagion modeling would enable policymakers and platform safety teams to act swiftly and strategically in containing harmful content before it escalates.

This research underscores the importance of adopting a symbol-aware approach to digital governance. Understanding the role of visual and cultural symbols in online communication is essential for building trustworthy, inclusive, and resilient digital public spheres. By embedding this awareness into policy and platform design, stakeholders can more effectively safeguard democratic discourse in an age increasingly shaped by algorithmic media and symbolic persuasion.

7. Conclusion

This study provides a detailed exploration of how symbolic content embedded in social media posts influences user engagement, perceptions of fairness, and the spread of information. Focusing on Taiwan's 2024 election-related anti-misinformation campaign, we examined the role of social, cultural, and political symbols using a combination of semiotic analysis, large language models, and epidemiological modeling. Through this interdisciplinary approach, we offer new insights into how visual communication shapes the dynamics of digital discourse.

The results show that posts containing symbolic elements, particularly those with cultural significance, tend to receive more user interaction and are perceived as more fair and trustworthy. These posts also spread more rapidly and widely compared to those lacking such content. The application of the SEIZ model further confirms that symbolic richness enhances the likelihood of content diffusion. These findings suggest that symbols serve not only as aesthetic or rhetorical devices but as central components in shaping trust and engagement in online environments.

The implications of these findings are relevant to platform moderation, public communication, and digital policy. Content moderation systems should move beyond purely text-based analysis to include visual and symbolic cues. Civic and governmental actors engaged in combating misinformation can improve their effectiveness by incorporating culturally resonant symbols into their campaigns. At the same time, policy frameworks should support transparent access to multimodal data and promote the inclusion of symbolic understanding in algorithmic audits and content governance strategies.

This research highlights the importance of developing analytical tools that are responsive to the complexities of multimodal digital content. As platforms continue to prioritize visual communication and generative AI becomes increasingly integrated into everyday online interactions, understanding the role of symbolic expression will become essential for maintaining trustworthy and inclusive information systems.

In conclusion, this work contributes to ongoing efforts to understand how information spreads and is perceived in digital spaces. By recognizing the influence of symbolic communication, stakeholders can build more resilient, fair, and informed public discourse across increasingly complex and visual online ecosystems.

8. Limitations and future work

While this study provides a comprehensive analysis of symbolic content in social media during Taiwan's 2024 anti-misinformation campaign, there are several limitations that should be acknowledged. First, the data collection was restricted to Instagram, which, although highly visual and widely used, represents only one platform among many where misinformation and counter-narratives circulate. The findings may not fully generalize to other platforms with different user behaviors, affordances, and content dynamics such as TikTok, X (formerly Twitter), or Facebook.

Second, the classification of symbols relied on the interpretive outputs of large language models, specifically GPT-4o and Gemini Pro Vision. While these models offer advanced multimodal capabilities, they are not free from limitations in cultural sensitivity or contextual accuracy. The symbolic interpretations are influenced by the training data and design of these models, which may introduce biases or misclassifications, especially for more subtle or region-specific symbols.

Third, the study focuses primarily on engagement metrics such as likes and the modeled diffusion of posts, without incorporating deeper behavioral indicators such as sharing, commenting patterns, or sentiment dynamics over time. These aspects could provide a more granular understanding of how symbolic narratives influence discourse and decision-making.

Future research should extend this framework across multiple platforms and cultural contexts to examine whether similar symbolic patterns emerge in different electoral or crisis situations. Comparative studies could explore how the same symbols are received differently across regions or demographics, revealing more about the interaction between symbolism and sociopolitical identity. Additional work could also refine the semiotic detection process by incorporating human-in-the-loop validation or expanding the scope of symbols to include audio and motion, especially on platforms where video dominates user interaction.

Moreover, integrating sentiment trajectory analysis and network diffusion patterns could provide a deeper view into how symbolic posts influence not only engagement but also belief formation and public opinion over time. As generative AI continues to shape content production, future studies should also investigate how synthetic symbolic content compares with authentic imagery in terms of influence and trustworthiness.

Expanding the methodological framework to include qualitative interviews or user surveys may further enrich our understanding of how audiences interpret and respond to symbolic elements. This would help validate model predictions and ground symbolic interpretations in real-world perception. As digital ecosystems evolve, continuing to study how meaning is constructed through symbols remains essential for building accountable and trustworthy communication infrastructures.

Data availability statement. Data availability: The data that support the findings of this study are openly available in Examining the Role of Semiotics in Social Media-driven Information Campaigns - Instagram Data at https://doi.org/10.5281/zenodo.15586828.

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Author contribution. M.G. conducted the analysis and drafted the manuscript. N.A. conceptualized the study, helped in ideation, helped with research design, methodology, and experiment set up, acquired funding, reviewed, and edited the paper.

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